ADAPTIVE APPROACH FOR CHANGE DETECTION IN EMG RECORDINGS

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Abstract-**In this paper we present a new algorithm to detect abrupt changes in a signal when there is no a priori knowledge of the hypotheses on the process to be detected. This algorithm is based on the CUSUM algorithm. It can be applied in case of frequency and energy changes. This algorithm works when the samples are dependant and autoregressive modeling is needed. It is used to distinguish EMG segments from noise segments.**
***Keywords* - Likelihood ratio, CUSUM, estimation, AR, EMG**

I. INTRODUCTION

Detection and segmentation of events in noisy random signals are classical problems of signal processing. When the parameters of the hypotheses are known, one of the most powerful algorithms is the CUSUM algorithm, which is based on the logarithm of likelihood ratio [1]. However, in most applications (including biomedical) the parameters of the hypotheses are unknown. Therefore it is necessary to propose a new approach to detect the changes in the signal [2][3].

In this paper, we present an algorithm for the segmentation of signals without a priori knowledge of the hypotheses on the process to be detected. The new method proposed in this paper achieves detection when the signals recorded are of long duration. This algorithm is based on the main idea of the CUSUM algorithm (designed for known hypotheses) but adapted to be applied for detecting change when the parameters of the signals are unknown. In the first paragraph, we present the CUSUM algorithm idea, which is based on the logarithm of likelihood ratio test between hypotheses. Our new algorithm is presented in the second paragraph in case of energy and frequency changes. Finally we will present an application on EMG signals.

II. CUSUM ALGORITHM

Let X= (x_1, x_2, …, x_t) be a series of independent observations up to time t. Our problem is to detect changes in this sequence. We shall assume that the probability density function of the process X depends on a parameter θ. The classical and optimal algorithm of this problem is the CUSUM (cumulative sum) algorithm proposed by Basseville and Nikiforov [1]. This algorithm consists of computing the difference between the value of the log-likelihood ratio and its current minimum value at each time t. The corresponding decision rule at each time t, is to compare this difference to a threshold h.

If f_{θ_0} and f_{θ_1} are the probability density functions of two hypotheses H_0 and H_1, the log-likelihood ratio is:

$$s_t = Ln\frac{f_{\theta_1}(x_t)}{f_{\theta_0}(x_t)} \tag{1}$$

The cumulative sum function is:

$$\mathrm{CS}_t = \sum_{i=1}^{t} s_i \tag{2}$$

The detection function is:

$$g_t = CS_t - \min_{1\le k\le t} CS_k \tag{3}$$

And finally the stopping time is:

$$t_a = \inf\{ t \ge 1 : g_t \ge h \} \tag{4}$$

The detectability of this algorithm is based on the sign $E(s_t)$.

We can demonstrate that:

$$\begin{aligned} E_{\theta_0}(s_t) &< 0 \\ E_{\theta_1}(s_t) &> 0 \end{aligned} \tag{5}$$

The concept of the CUSUM algorithm is illustrated in Fig. 1.

III. THE NEW ALGORITHM

A. Introduction

When the parameters of the two hypotheses are unknown we cannot use the CUSUM algorithm directly (θ_0 and θ_1 are unknown). Our new algorithm is based on two adaptive sliding windows W_0 and W_1 used to estimate θ_0 and θ_1 at each time t.

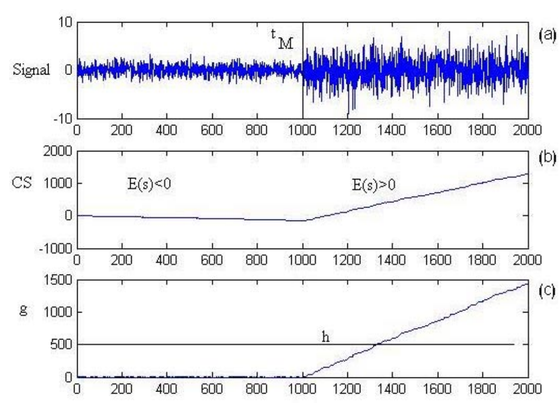

Fig. 1. Illustration of the CUSUM algorithm. (a) A signal which changes at time t_M; (b) Evolution of CS; and (c) Evolution of the decision function g_t.

These windows are chosen as demonstrated in Fig. 2.

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Adaptive Approach for Change Detection in EMG Recordings	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Lebanese University Faculty of Engineering I Tripoli, Lebanon	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

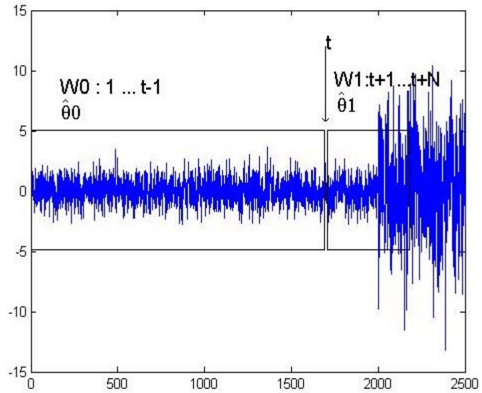

Fig. 2. Definition of windows in the new approach

$$\begin{cases} W_0 : 1 \,.....\, t-1 \rightarrow \hat{\theta}_0 \\ W_1 : t+1 \,.....\, t+N \rightarrow \hat{\theta}_1 \end{cases} \qquad (6)$$

x_t is not used to estimate $\hat{\theta}_0$ and $\hat{\theta}_1$,which are used to compute s_t.

The adaptive log-likelihood ratio in this case is:

$$\hat{s}_t = Ln \frac{f_{\hat{\theta}_1}(X_t)}{f_{\hat{\theta}_0}(X_t)} \qquad (7)$$

The adaptive CUSUM is:

$$\mathrm{ACS_t} = \sum_{i=1}^{t} \hat{s}_t \qquad (8)$$

The new decision function is:

$$g_t = ACS_t - \min_{1 \le k \le t} ACS_k \qquad (9)$$

The new idea in our algorithm is to use two threshold values h_l and h. h_l is used to stop the estimation of θ_0 when H_1 begins.

The flowchart of our algorithm is presented in Fig. 3.

B. Detectability of the New Algorithm

It can be shown in our new algorithm that:

$$\begin{aligned} E_{\theta_0}(s_t) < 0 \\ E_{\theta_1}(s_t) > 0 \end{aligned} \qquad (10)$$

As in case of the CUSUM algorithm, this property is very important to verify whether the new approach can detect changes or not. There are two considerations needed to verify this point:

a)- If no change occurs in the signal, when t tends towards infinity $\hat{\theta}_0$ is close to θ_0, and $\hat{\theta}_1$ is an estimation of θ_0.

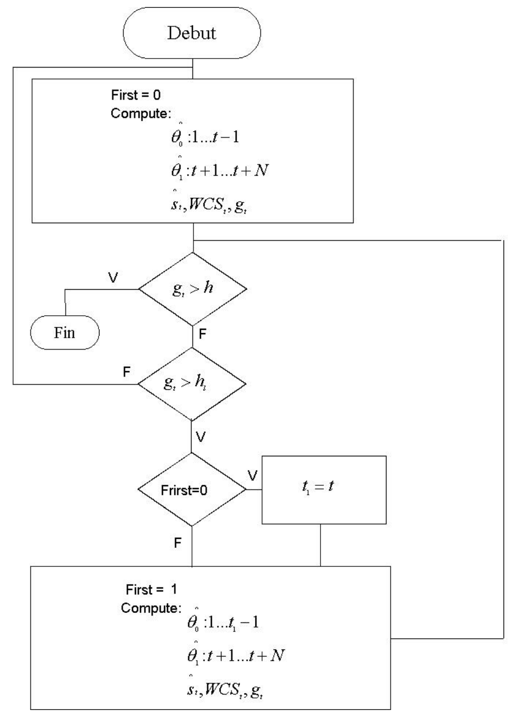

Fig. 3. Flowchart of the new approach

In this case:

$$E(\hat{s}_t) = E(\ln \frac{f_{\hat{\theta}_0}(x_t)}{f_{\theta_0}(x_t)}) < 0 \qquad (11)$$

b)- If a change occurs in the signal $\hat{\theta}_0$ is an estimation of θ_0 and $\hat{\theta}_1$ is an estimation of θ_1.

In this case:

$$E(\hat{s}_t) = E(\ln \frac{f_{\hat{\theta}_1}(x_t)}{f_{\hat{\theta}_0}(x_t)}) > 0 \qquad (12)$$

We note that the new algorithm conserves the property of the detectability of CUSUM algorithm.

IV. Detection of Energy Changes

In the case of energy changes, we assume that the samples are independent and that:

$$f_{\theta_0}(x_t) = \frac{1}{\sigma_0 \sqrt{2\pi}} e^{-\frac{1}{2\sigma_0^2} x_t^2} \qquad (13)$$

$$f_{\theta_1}(x_t) = \frac{1}{\sigma_1 \sqrt{2\pi}} e^{-\frac{1}{2\sigma_1^2} x_t^2} \qquad (14)$$

The log-likelihood ratio of s_t can then be expressed as:

$$\hat{s}_t = \frac{1}{2}\ln\frac{\hat{\sigma}_0^2}{\hat{\sigma}_1^2} + x_t^2\left(\frac{1}{2\hat{\sigma}_0^2} - \frac{1}{2\hat{\sigma}_1^2}\right) \tag{15}$$

$\hat{\sigma}_0^2$ and $\hat{\sigma}_1^2$ are estimated using W_0 and W_1.

V. Detection of Frequency Changes

In biomedical applications, the changes can affect signal energy and frequency. In this case the CUSUM algorithm can not be used because the samples of the signal are dependent, therefore AR modeling is needed. The probability density function of the signal for AR modeling is:

$$f_\theta\ (x_t / x_1, x_2, ..., x_{i-1}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}\varepsilon_t^2} \tag{16}$$

Where $\varepsilon_t = \sum_{i=0}^{p} a_i x_{t-i}$, (ε_t) is a Gaussian white noise sequence with variance σ^2.

To apply our algorithm for AR modeling, three windows are needed:

$$\begin{cases} W_0 : 1 \ ..... \ t-p-1 \rightarrow \hat{\theta}_0 \\ W_1 : t+1 \ ..... \ t+N \rightarrow \hat{\theta}_1 \\ W_p : t-p \ ... \ t \rightarrow \hat{s}_t \end{cases} \tag{17}$$

These windows are interpreted in Fig. 4.

In case of AR modeling, $\hat{\theta}_0 = (a_1^0, ..., a_p^0, \sigma_0^2)$ and $\hat{\theta}_1 = (a_1^1, ..., a_p^1, \sigma_1^2)$.

The log-likelihood ratio is:

$$\hat{s}_t = Ln\frac{f_{\hat{\theta}_1}(x_t / x_{t-1}, x_{t-2}, ..., x_{t-p})}{f_{\hat{\theta}_0}(x_t / x_{t-1}, x_{t-2}, ..., x_{t-p})} \tag{18}$$

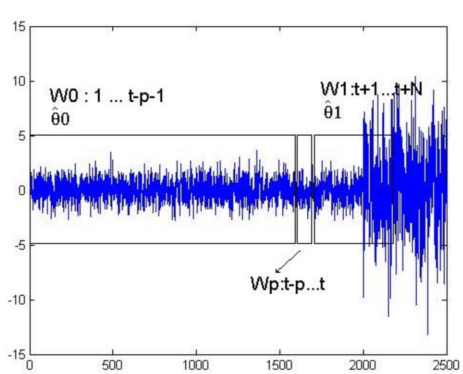

Fig. 4. Definition of windows in the case of AR modeling. W_0 : used to estimate θ_0, W_1 : used to estimate θ_1

The adaptive CUSUM is:

$$\mathrm{ACS_t} = \sum_{i=1}^{t} \hat{s}_t \tag{19}$$

The decision function is:

$$g_t = ACS_t - \min_{1\le k\le t} ACS_k \tag{20}$$

The value of s_t can be expressed as:

$$s_t = \frac{1}{2}\ln\frac{\sigma_0^2}{\sigma_1^2} + \frac{(\varepsilon_t^0)^2}{2\sigma_0^2} - \frac{(\varepsilon_t^1)^2}{2\sigma_1^2} \tag{21}$$

By applying this formula we can detect both energy and frequency changes.

VI. Results

A- Results on Simulated Signals

Detection algorithms were first applied on simulated signals in order to study the performance of the algorithm. For that purpose, signal segments were generated using Gaussian white noise filtered by a bandpass filter at different central frequencies and identical bandwidth BP. Each H_j corresponded to a bandpass filtered signal with a central frequency f_j.
As shown in Fig. 5., the method can detect different segments in a simulated signal.

B- Results on EMG Signals

An EMG signal contains information about muscular activity. The characteristics of the signal depend on the physiological conditions and the recording environment. To process an EMG signal, it is necessary to identify the parts of a signal when the muscle is active. The muscle is active in the 4th segment of Fig. 5. Our aim is to detect these segments and to separate all EMG activity.

The detection of the segments in the EMG signals are shown in Fig. 6.

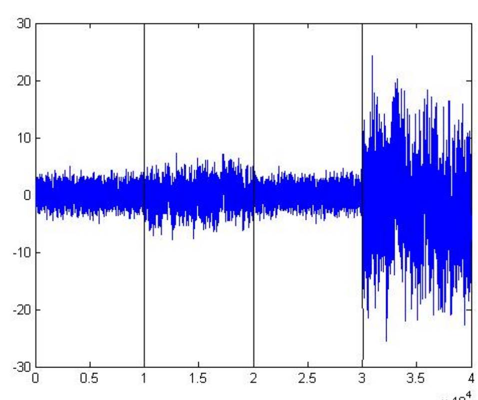

Fig. 5. Detection result on a simulated signal.

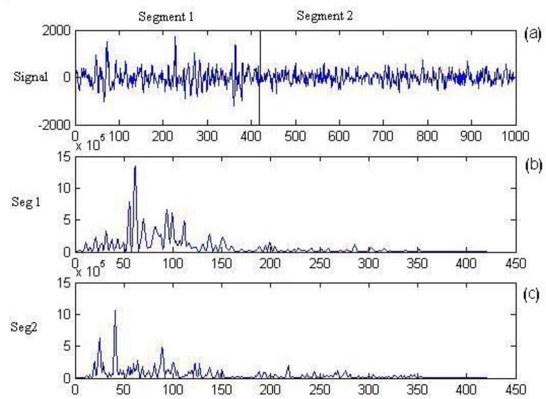

Fig. 6. Detection of segments in an EMG signal:
(a) A signal that contains two segments Seg_1 and Seg_2;
(b) The spectral density of Seg_1; and (c) The spectral density of Seg_2

VII. Conclusion and Persepective

In this paper we presented a sequential segmentation algorithm method applied without a priori knowledge on the parameters of the hypotheses to be detected.

Our new algorithm is based on the log-likelihood ratio between two instantaneous hypotheses estimated at each time t. It is used when the changes affect the energy and the frequency of the signal. When applied on simulated signals it produced a satisfactory segmentation.

This algorithm has to be augmented with additional processing in order to classify EMG signals and to identify the corresponding physiological events.

Acknowledgment

We would like to thank the Lebanese CNRS for the financial support of this project.

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